

Grid Integration of Distributed Wind Generation: A Markovian and Interval Approach

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Introduction

- This work develops a synergistic combination of Markovian and interval optimization for unit commitment problems with wind generation and transmission
- Motivation: Important to accommodate high penetration of wind
- DOE's goal: 20% wind by 2030
- Obama's goal: 80% clean energy by 2035
- In Spain, an unprecedented decrease in wind generation in Feb. 2012 is equivalent to the sudden down of 6 nuclear plants (4 is not unusual)
- Texas Emergency Electric Curtailment Plan is called on in Feb. 2008
- Difficulties:
- Intermittent/uncertain nature of wind generation
 - Cannot be dispatched as conventional units
 - Large uncertainty: Mean Absolute Error (normalized over capacity) of dayahead wind power forecast: 15%~20%
- Complicated structures of transmission networks
- Computational complexity: NP hard problems

Literature Review

- Stochastic programming
- Modeling wind generation Representative scenarios
- To minimize the expected cost over scenarios
- Difficult to choose an appropriate number of scenarios to balance computational complexity and solution feasibility
- Robust optimization
 - Uncertainties modeled by an uncertainty set w/o probabilities
 - To optimize against the worst-case realization
 - Min Max conservative and computationally challenging
- Pure interval optimization [1]
- Modeling wind generation Closed intervals w/o probabilities
- Capturing the bounds of uncertain inputs in different types of constraints,
 and making decisions feasible for these bounds
- System demand constraints: As long as min. and max. wind realizations are feasible, other realizations within them will be feasible
 - E.g., wind farm 1 outputs [10 MW, 40 MW], and wind farm 2 [20 MW, 50 MW]. Total wind generation = [30 MW, 90 MW].
 - System demand = 200 MW. Net system demand = [110 MW, 170 MW]
 - If a set of committed units with p_i^{min} and p_i^{max} can meet the 110 MW and 170 MW, can it satisfy possible demand at 140 MW?
- Transmission capacity constraints: |Power flow| $\leq f_l^{max}$
 - A line flow is a linear combination of nodal injections weighted by generation shift factors (GSFs can be + or -)

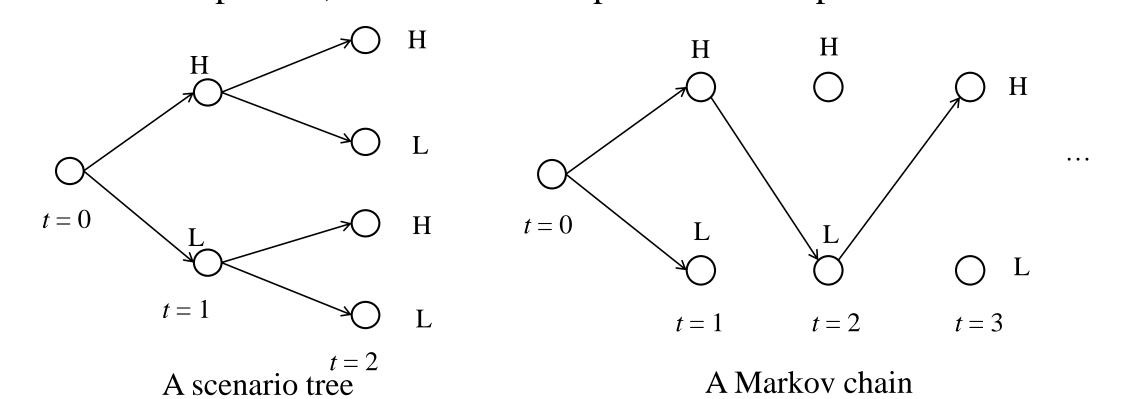
 $f_l(t) = \sum_{i} a_l^i \left(p_i^I(t) + p_i^W(t) - p_i^L(t) \right), \forall l, \forall t$

"Passively" capture bounds of uncertain inputs $\sum_{i} a_{l}^{i} p_{i}(t) \leq f_{l}^{\max} - \max \left[\sum_{i} a_{l}^{i} \left(p_{i}^{W}(t) - p_{i}^{L}(t) \right) \right], \forall l, \forall t$ Pre-computed based on interval arithmetic

- Objective function: To minimize the cost of the expected realization
- Linear and efficient via interval arithmetic; conservative

Previous Work - Markovian Optimization w/o Transmission [2]

- Model aggregated wind generation A Markov chain
 - Given the present, the future is independent of the past



- N^T possible scenarios at one node
- at one node $T \cdot N$ possible states at one node
- Advantage: State at a time instant summarizes the information of all previous instants in a probabilistic sense for reduced complexity
- Stochastic UC depends on states instead of scenarios

Markovian and Interval Unit Commitment

- Wind model considering transmission constraints
 - With congestion, wind generation cannot be aggregated together
 - Wind states for farms at different nodes may not be the same
 - Nearby wind farms: Generation aggregated
 - Wind farms far apart: States assumed independent
 - A Markov chain per node
 - With I wind nodes (Markov chains): N^I possible global states at time t
 - Curse of dimensionality!

Key idea: Markov + interval-based optimization

- Markovian analysis to depend on local states; interval analysis to manage extreme combinations of non-local states
 - Local state: Wind generation state at the node under consideration (will be extended into zonal state in future work)
- Physical infrastructure supporting this idea: Wind-diesel system
- How to combine two distinct approaches? Divide the generation (dispatch decision) of a conventional unit into two components

• *Markovian component* depends on the local state n_i

$$x_{i}(t)p_{i}^{\min} \leq p_{i,n_{i}}^{M}(t) + p_{i,\overline{n}_{i}}^{I}(t) \leq x_{i}(t)p_{i}^{\max}, \forall i, \forall t, \forall n_{i}, \forall \overline{n}_{i}$$

$$(3)$$

- Interval component manages extreme combinations of non-local states
- Constraints innovatively formulated to guarantee solution feasibility for all realizations without much complexity
- The effective use of local wind states alleviates the over-conservativeness of interval optimization
- System demand constraints
 - Based on interval optimization ^[1]: As long as min. and max. global states are feasible, all other realizations within them will be feasible

$$\sum_{i} \left(p_{i,\min n_{i}}^{M}(t) + p_{i,\underline{m_{i}}}^{I}(t) \right) = \sum_{j} \left(p_{i}^{L}(t) - p_{i,\min n_{i}}^{W}(t) \right), \forall t$$

$$\text{minimum local} \qquad \text{The minimum combination of non-local states (where}$$

node i other nodes are at their minimum possible states) $\sum \left(p_{i,\max n_i}^M(t) + p_{i,M_i}^I(t)\right) = \sum \left(p_i^L(t) - p_{i,\max n_i}^W(t)\right), \forall t \tag{5}$

- Transmission capacity constraints: |Power flow| $\leq f_l^{max}$
- Flexibility of local conventional generation used to shrink ranges of RHS

$$\sum_{i} a_{l}^{i} p_{i}^{I}(t) \leq f_{l}^{\max} - \max \left[\sum_{i} a_{l}^{i} \left(p_{i,n_{i}}^{W}(t) + p_{i,n_{i}}^{M} - p_{i}^{L}(t) \right) \right], \forall l, \forall t$$

$$\text{Markovian nodal injection} \equiv P_{i,n_{i}}^{M}(t)$$

$$\text{(containing decision variables)}$$

- Ramp rate constraints
 - Required for possible local states, local state transitions, $p_{i,m_i}^I(t)$, and $p_{i,M_i}^I(t)$
- The objective function: To approximate the expected cost w/o much complexity
 - A weighted sum of extreme realizations and the expected realization

$$\min \sum_{t=1}^{T} \sum_{i=1}^{I} \left\{ \sum_{n_i=1}^{Ni} \left[w_{n_i,m_i}(t) C_i \left(p_{i,n_i}^M(t) + p_{i,m_i}^I(t) \right) + w_{n_i,M_i}(t) C_i \left(p_{i,n_i}^M(t) + p_{i,M_i}^I(t) \right) \right] \right\}$$

$$w_E(t) C_i \left(p_{i,E}(t) \right) + u_i(t) S_i + x_i(t) S_i^{NL} \right\}$$
Weights adding up to 1

- A non-linear MIP formulation
 - Non-linearity lies in max/min (negative flow direction) operations in (6)

Solution Methodology - Branch-and-cut

- Max/Min operations transformed into a linear form
- Idea: Analyze the monotonicity of Markovian nodal injections w.r.t. local states, then select indices of local states w/o optimization
- The Monotonicity Conjecture: The local state with lower wind generation provides less or equal Markovian nodal injection at the optimum, i.e.,

$$P_{i,n_{i}-1}^{M}(t) \le P_{i,n_{i}}^{M}(t), \forall i, \forall t, \forall n_{i}, \forall (n_{i}-1) \in \{n_{i}-1 \mid \varphi_{n_{i}-1}(t) > 0\}.$$
(8)

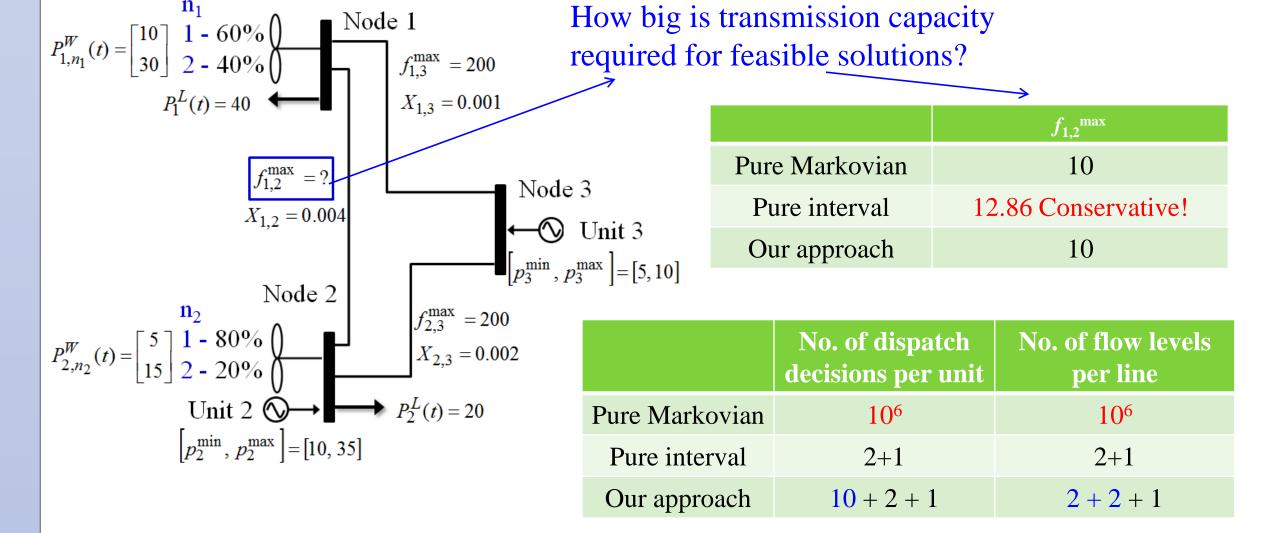
• Generalized monotonicity analysis used to support this conjecture

$$\max_{n_i} P_{i,n_i}^M(t) = P_{i,\max n_i}^M(t), \qquad \min_{n_i} P_{i,n_i}^M(t) = P_{i,\min n_i}^M(t), \forall i, \forall t.$$
 (9)

- Overall problem converted linearly after
- Including (8) as constraints
- Substituting the min/max operations with corresponding states
- State transition matrices given and state probabilities pre-computed

Numerical Testing Results

- CPLEX 12.5.1.0 on a PC laptop with an Intel Core(TM) i7-2820QM 2.30GHz CPU and 8GB memory
- Illustrative examples
 - Conservativeness Consider 3 nodes, 2 wind farms, 2 units, and 1 hour



- Complexity Consider 6 wind farms at different buses, 10 states for each
- Solution feasibility and modeling accuracy
 - IEEE 30-bus system with 2 wind farms at 40% wind penetration
 - Free wind curtailment and load shedding at \$5,000/MWh penalty
 - Stopping MIP gap 0.1% and then 10,000 Monte Carlo runs
 - Our approach provides 5.23% lower simulation cost than pure interval
 - Our approach is the most accurate, as it has the smallest APE#

Approach		Deter.	Interval	Ours
Optimization	CPU time	2s	53s	1min53s
	n Cost (k\$)	248.66	280.67	253.40
	Penalty (k\$)	0	0.47	0.01
UC	UC cost (k\$)		67.72	65.22
Simulation	E(Cost) (k\$)	314.89	263.26	250.17
	APE#	21.03%	6.61%	1.29%
	STD(cost) (k\$)	74.46	33.77	35.13
	Penalty (k\$)	40.82	0	0

Absolute percentage error (APE) = |optimization cost – simulation cost| / simulation cost \times 100%)

- Computational efficiency
- IEEE 118-bus systemwith 3 wind farms

		Ours
	CPU time	41s
Optimi- zation	MIP GAP	0.01%
Zation	Cost (k\$)	911.48
UC Cost (k\$)		12.83
Q1 1	E(cost) (k\$)	920.97
Simula- tion	APE	1.03%
uon	STD(cost) (k\$)	24 64

Conclusion

- An important but difficult issue
- Hybrid Markovian and interval optimization to overcome the complexity caused by transmission constraints
 - Markovian analysis to depend on local state/reduce conservativeness
 - Interval analysis to ensure feasibility against realizations
- Problem transformed into a linear form based on monotonicity, and then solved efficiently by using branch-and-cut
- Opens a new and effective way to address stochastic problems w/o scenario analysis and avoid over-conservativeness

References

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- 3. Y. Yu, P. B. Luh, E. Litvinov, T. Zheng, F. Zhao, and J. Zhao, "Grid integration of distributed wind generation: A Markovian and interval approach," submitted.

